TECHNOLOGY

DIFFERENT APPROACHES ARE BEING TRIED; SOME HAVE ALREADY BEEN COMMERCIALIZED

Gap closing between fuzzy, neural nets

BY R. COLIN JOHNSON

San Diego — Research organizations in the United States, Japan and Europe are bridging the gap between fuzzy logic and neural networks. Though the science of marrying the two "smart" technologies is relatively new, researchers have already developed a myriad of approaches and have even commercialized a few.

At last month's IEEE-sponsored International Conference on Fuzzy Systems here, 42 of the 180 papers presented centered on ways to merge fuzzy and neural technologies. And in recognition of the trend, the IEEE next year will do some merging of its own, combining its neural and fuzzy conferences.

This year's conference provided a forum for all known approaches, which build on the pioneering work of such theorists as University of Southern California professor Bart Kosko (see sidebar). Kosko and others began experimentally combining fuzzy logic and neural networks more than two years ago (see March 4, 1991, page 35; Sept. 24, 1990, page 98). The conference results will be published in a fall issue of the IEEE's *Neural Networks* magazine.

In the United States, microchips that combine fuzzy logic and neural networks are already available from American NeuraLogix Inc. (Sanford, Fla.; see June 10, page 45). In Japan, the first microchip to add neural abilities to a fuzzy system is the "fuzzy neuron" chip, invented by Takeshi Yamakawa, director of the Fuzzy Logic Systems Institute (Iizuka). Apollo Electronics Co. Ltd. (Fukuoka, Japan) is fabricating the fuzzy-neuron chip in conjunction with the Kyushu Institute of Technology, where Yamakawa is a professor.

Up from transistors

Apollo Electronics has been working with Yamakawa since 1989. "We have a 40 percent share of the transistor market in Japan, but it is clear that to get more share is very difficult in this kind of product," said Apollo deputy director Masanari Oh, explaining the company's move into fuzzy neural technology.

Using discrete transistors, Yamakawa demonstrated to Apollo Electronics that his fuzzy neuron could automatically assay dental work (see Aug. 20, 1990, page 1). The application judged a patient's dental work from impressions it had learned were good examples of oral architecture. Since then, Apollo Electronics has verified the utility of the fuzzy neuron for motor-control applications. In June, it saw first silicon on the microchip version, which will appear commercially later this year.

Takeshi Yamakawa, left, worked with Masanari Oh on Japan's first neural-fuzzy chip.

Yamakawa told a conference audience that the software for his technology "eliminates the need for an expert when designing a fuzzy neuron for a particular application," thus making the approach accessible to a broad variety of end users.

Another Japanese laboratory working to meld fuzzy and neural technologies is the Laboratory for International Fuzzy Engineering Research (Yokohama). LIFE is working with Chiba (Japan) University and the University of Tokyo on its approach, which bears the hopeful name Famous (fuzzy associative memory organizing unit systems).

Famous integrates an associative memory built from neural technology with a fuzzy knowledge base from which inferences can be made. Its trial application is in helicopter control.

Famous houses two types of knowledge—dynamic and static—in a hierarchical database. Dynamics for a helicopter controller might include a circular approach pattern when holding at an airport. Static knowledge for a helicopter would include hovering.

Pilots' fuzzy knowledge was initially imparted to Famous through the pilot's completion of simple if-then statements about flying (for example, "If the nose is a little too far down, then pull back on the stick a little.") That initial knowledge was subsequently refined by a neural-learning method. As a result, the vehicle's autonomous capabilities exceeded those of live pilots, according to a LIFE demonstration using a model helicopter with four independent fans.

Fuzzy mimics neural

The fuzziest approach to marrying the technologies was proposed by Pei-zhuang Wang, a professor at the National Institute of Singapore and chairman of Aptronix Inc. (San Jose, Calif.). Wang and fellow professors S.Z. He, S.H. Tan and C.C. Hang described a method for adding neural-like adaptiveness to fuzzy systems.

Other approaches, such as LIFE's, begin with a fuzzy system that has been coarsely defined by experts. That fuzzy rule base is then refined with a neural network that adapts to minimize errors. The problem with such approaches, according to Wang, is that good results are not guaranteed, since the neural-learning mechanisms are not well understood.

Instead, Wang advocates beginning with a set of fuzzy rules that have been well-tuned by an engineer using trial-and-error methods. A neural-like adaptivity mechanism is then installed in the fuzzy system to handle exceptional circumstances after the system has been deployed. The resulting fuzzy systems, according to the authors, can compensate not only for variable loads but also for wear and tear on machinery over time.

Instead of adding a popular neural learning mechanism, Wang and associates generate two internal fuzzy variables within their systems. The two variables detect output errors and how rapidly the errors change. A single parameter is then automatically tuned to adjust the relative influence of the two fuzzy variables as a system runs. By shifting its internal fuzzy map slightly in response to output errors and changes in those errors, the total system output can be kept on track, according to the authors.

Neural mimics fuzzy

At the other end of the spectrum from imparting neural-like learning to fuzzy systems are approaches that impart fuzzy-like logic to neural networks. Proponents claim that by giving the neural network knowledge of fuzzy operations, the network can adapt in a more intelligent manner than with homemade algorithms such as Wang's.

One paper proposed creating a "min/max neural network" with built-in fuzzy min/max operations. Yoichi Hayashi at Ibaraki (Japan) University—along with colleagues Ernest Czogola of the Technical University of Silesia (Gliwice, Poland) and James Buckley of the University of Alabama in Birmingham—built fuzzy operations into the learning method used by the fuzzy neural controller (a modified version of the popular delta learning rule used by other neural models). The resulting min/max neural network learns to simulate a fuzzy controller but with rules that can be automatically tuned by a neural learning method.

Throwing in yet another smart technology, IBM Corp. described progress in evolutive learning—the use of genetic algorithms to combine fuzzy and neural systems automatically.

Evolutive learning combines inductive learning—via synaptic weight adjustment of a neural network—with deductive learning through the modification of the network topology with a genetic algorithm. The re-

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It computes: fuzzy plus neural

A mix of fuzzy logic and neural learning can solve most computational tasks, according to a paper presented at the recent International Conference on Fuzzy Systems, held in San Diego and sponsored by the IEEE.

"The key to fuzzy approximation is to add the outputs of your rule sets," said the paper's author, University of Southern California professor Bart Kosko. Older fuzzy systems take the point-wise maximum of multiple outputs from fuzzy sets and that yields the envelope of all outputs. "But maxing the outputs converges to a flat line as more rules are added, and that washes out the information gained when several rules fire at once in large systems."

Adding outputs solves the problem by invoking what Kosko calls the central-limit theorem, which converges to a normal bell curve, as expected. In an additive fuzzy system, the more rules that fire, the sharper the output bell curve becomes and, therefore, "the more sensitive the system is to input changes," Kosko explained.

Kosko pioneered combining neural learning methodologies with fuzzy systems (see Aug. 27, page 29), helping to spawn dozens of research projects that combine Rsmart technologies worldwide (see related story).

Formal proof

Formally, Kosko's paper proved that additive fuzzy systems can approximate *any* continuous function or input-output relationship. Each fuzzy if-then rule defines a sausage-shaped patch in the input-output space. By stringing these patches together like linked sausages, they can cover and thus approximate an entire function. His theorem shows that engineers can pick the error level in advance between a fuzzy system and the function it approximates. In theory, engineers can always find a finite set of rules that satisfies any error limit.

But can you always find the fuzzy rules in practice? "That's where neural learning comes in," Kosko said. "Unsupervised neural learning estimates the patches [rules], and the patches estimate the function. The more data you have, the better the neural system estimates the rules." —*R. Colin Johnson*

Fuzzy, neural nets gap grows smaller

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sult, according to IBM, is the automatic adaptation of system knowledge to the problem domain.

The evolutive learning method uses a fuzzy criterion based on entropy to select the neural-network architecture best suited to a given problem area. The system automatically fits fuzzy rules into the neural network as appropriate to the problem domain, according to researcher Ricardo Jose Machado of IBM's scientific center in Rio de Janeiro, Brazil. IBM is conducting the research in conjunction with Unicamp (Campinas, Brazil), a biological institute.

Bucking the trend to add neural to fuzzy or vice versa, Fujitsu Ltd. (Kawasaki, Japan) proposed leaving the two types of systems separate and converting from one to the other as convenient, in a method that the company claims incurs no loss in functionality.

Fujitsu's modus operandi—as described by Akira Kawamura, Nobuo Watanabe, Hiojuki Okada and Kazuo Asakawa—first creates a fuzzy system by having experts fill out if-then questionnaires. It then converts that fuzzy system into a neural network, which is applied to the problem area and allowed to learn and thereby refine its model. After the neural system has been perfected to any user-specified degree of accuracy, it is converted back into a fuzzy system so its rules can be studied.

According to Fujitsu, the approach reveals many interrelationships among control variables that remain hidden within a neural network. Usually, the internal structures of a trained neural network are as inscrutable as real brain structures. But converting the network to a fuzzy system allows the equivalent set of fuzzy rules to be analyzed.

And the system can always be converted back into a neural network for deployment or for expansion of its training.

Silicon magnetic sensors

Plymouth, England — Researchers at the Polytechnic Southwest's Centre for Research in Information Storage Technology here have pioneered a technique for producing magnetic sensors on silicon substrates that are both smaller and more accurate than conventional electro-optic compasses and that can be manufactured at low cost.

The sensors are made using RF sputtering to deposit very thin layers of nickel iron permalloy on to a borosilicate substrate, then etching the necessary structures. The active layers are separated by silicon dioxide insulator layers. A series of snake-like structures act as magneto-resistive elements. Outputs from these elements are then linked to give a heading angle in degrees.

Kevin Stewart, who has been working on the project, explained that the device now occupies an area 1 mm square, but it is now being shrunk to around 100 um square. The device has an accuracy of 0.5 degrees and requires a drive current of 5 mA.

The work is funded by Aeronautical and General Instruments Ltd. Paul Thorneycroft, project manager, said they will design a hybrid device, including the sensor and its drive electronics, later this year. A fully integrated VLSI device is planned for 1993.

—*Simon Loe*